Binarization of Gray-Scaled Digital Images Via Fuzzy Reasoning

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Abstract - A new fast-computational technique based on fuzzy entropy measure has been developed to find an optimal binary image threshold. In this method, the image pixel membership functions are dependent on the threshold value and reflect the distribution of pixel values in two classes; thus, this technique minimizes the classification error. This new method is compared with two of the best-known threshold selection techniques, Otsu and Huang-Wang. The performance of the proposed method supersedes the performance of Huang-Wang and Otsu methods when the image consists of textured background and poor printing quality. The three methods perform well but yield different binarization approaches if the background and foreground of the image have well-separated gray-level ranges.

1. Introduction

Binary image processing is of special interest because an image with binary format can be processed with very fast logical (Boolean) operators. Since most image display systems and software assume images of 8 or more bits per pixel, the binarization of these images usually takes 2 extreme gray tones, black and white, which are ordinarily represented by 0 or 255, respectively, in an 8-bit gray-scale display environment.

Usually a binary image is obtained from an 8-bit gray-level image by thresholding and assigning the low binary (0) and high (255) values to all gray levels based on the chosen threshold. Obviously, the threshold that is chosen has a critical importance since it controls the binary-based pattern classification that is obtained from the gray-level image. The key issue is to choose an optimal threshold so that the number of misclassified image pixels is kept as low as possible. Image thresholding is the simplest image segmentation approach. It is actually a pattern classification procedure in which only one input feature is involved, the pixel intensity value. The key issue here is to choose an optimal threshold value so that the number of misclassified image pixels is kept as low as possible.

Fuzzy logic is a powerful tool to solve many image processing problems because of its ability to deal with ambiguous data. Selection of a threshold to binarize an image is not straightforward because of ambiguity or fuzziness caused by the overlapping of two class densities. Several fuzzy-model-based methods have been developed in the past and recently to overcome the difficulties. For example, an optimal threshold value can be determined based on Pal and Rosenfeld's fuzzy compactness measure and Pal and Ghosh's index of area coverage measure [1], [2]. In these two methods, for each possible threshold-value in the gray-scale range (0 to 255 range for an 8-bit gray-scale image), the membership value of every pixel is needed to compute the compactness or index of area coverage measure. When the image is large in size, these methods can

require a long computing time to search for the optimal threshold value. Huang and Wang recently developed a fuzzy thresholding algorithm that uses the image pixel value histogram but does not need to deal with each individual pixel [3]. This method can be very efficiently implemented and requires much less computing time than the above fuzzy-based methods. We have used Huang-Wang method as one of the image preprocessing operators within the implementation of a Visual Anomaly Detection Prototype System built for NASA at the Kennedy Space Center [4]. Another widely used and well-known digital image binarization method is Otsu's method, which is based on discriminant analysis to maximize some measures of class separability [5].

Similar to the Huang-Wang method, the proposed fuzzy reasoning image binarization approach uses the entropy measure as the criterion for selection of the optimal image threshold. Experimental results using real images via a PC with 1.8-GHz 1-GB capabilities showed that the proposed fuzzy thresholding method performed more reliably than Huang-Wang's and Otsu's methods for different types of images. Central processing unit (CPU) execution time is also a very important factor when using a given image binarization method in real-time systems; the proposed method, in general, requires similar CPU execution time to Otsu's method and much less execution time than Huang-Wang's method.

2. Implementation

In the proposed method, described in appendix A, we consider an image as an array of singletons corresponding to image pixels (see equation I, appendix A), each having a membership value associated with a property of the pixel, the grayness level. For image thresholding, the membership function is defined in terms of the grade of pixel's grayness belonging to one of the two classes, background and foreground, as shown in appendix A, figure 1. The membership function is calculated via a triangular function at each of the two classes (see appendix A, equation 4); the triangular function in each of the two classes is built using the average image grayness and histogram-based weight values at each class as shown in appendix A, equations 2 and 3. In each of the two classes, the membership value (equal to I) is the largest at the class average gray level and reduces its value when the difference between the pixel gray level and its class average level increases. This means that pixels with gray levels close to their corresponding class average gray levels have less fuzziness or ambiguity and thus can be classified with greater confidence than pixels with gray levels far from their class gray levels. The image entropy measure is used as a cost function to find the optimal threshold (equation 6). It is defined using the histogram information as shown in appendix A, equation 5. The entropy factor needed to compute the entropy measure is calculated using a simple and fast computational linear function as shown in appendix A, figure 2.

The proposed method uses a similar but more efficient and faster computational approach than the one used in Huang-Wang method. Huang-Wang method uses a symmetric membership function, while the proposed approach uses a more realistic membership function having the highest and lowest gray levels holding nonzero histogram values as the domain limits. Huang-Wang method limits the membership values within a range of 0.5 to 1.0 since it uses Shanon's entropy function as a cost

function and the cost should decrease as the membership function value increases (as the fuzziness becomes smaller); Huang-Wang method allows the use of Shannon function in the range of 0.5 to 1.0 since the Shannon function values decrease only within this range as the membership value increases. This is why Huang-Wang method imposes this restriction to the membership function. In contrast, the new proposed method does not restrict the range of membership values and uses a straightforward triangular-type membership function. The proposed approach also uses a straight-line cost function that requires much less computational power than the Shannon function used by Huang-Wang method.

3. Examples

The performance of the proposed thresholding method was compared to Huang-Wang and Otsu methods, two of the most reliable image threshold methods, using 4 different 8bit gray-scale images as shown in figures I and 2. The binary threshold results for each image using Otsu, Huang-Wang, and the proposed method are shown in figures 3, 4, 5, and 6. Figure 7 summarizes the CPU execution time required by each threshold method to find the optimal threshold and generate the respective binary image. For images with textured background and poor printing quality (images 1 and 4), the proposed method has a consistently better overall binarization performance than Huang-Wang and Otsu methods, as shown in figures 3 and 6; the CPU execution time for the proposed method is in general much lower than the CPU time required by Huang-Wang method and almost the same as the CPU execution time required by Otsu's method, as illustrated in figure 7. In images 2 and 3 (figures 4 and 5, respectively) the Huang-Wang and the proposed methods yielded similar binarization performance, but the proposed method requires less CPU execution time. In image 3 (figure 5), the Otsu method yielded a different binarization performance than the other two methods (Wang-Huang and the proposed one), requiring similar CPU execution time to the proposed method. While Otsu's method successfully extracted the general borders of image 3, the other two methods (Huang-Wang and the proposed one) extracted a relevant part of the image (the numbers printed on the compact disk).

In general, the proposed and Otsu methods require comparable CPU execution time, while the Huang-Wang method requires much more CPU execution time, as shown in figure 7. The performance of the proposed method supersedes the performance of Huang-Wang and Otsu methods when the image consists of textured background and poor printing quality. The three methods perform well but yield different binarization approaches if the background and foreground of the image have well-separated gray-level ranges.

4. Conclusions

The proposed thresholding method supersedes Huang-Wang and Otsu methods, the most reliable and fastest thresholding methods, when the image contains textured background and poor printing quality (see figures 3 and 6). This would provide a much simpler, faster, and more reliable binary segmentation tool for Optical Character Recognition (OCR) and Optical Character Validation (OCV) applications and texture analysis. This method would also provide fast and reliable segmentation capability to extract certain

areas of interest (see figures 4 and 5), reducing considerably the CPU execution time required to extract them using existing gray-scale-based approaches. Since the proposed method requires relatively low computational time compared with Huang-Wang and Otsu methods, it might be used as a binarization operator within real-time image analysis systems.

References

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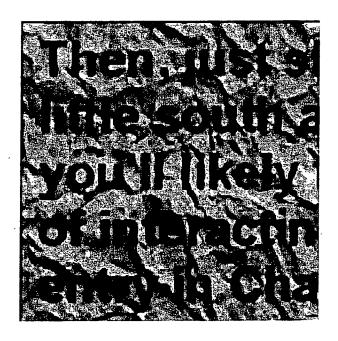
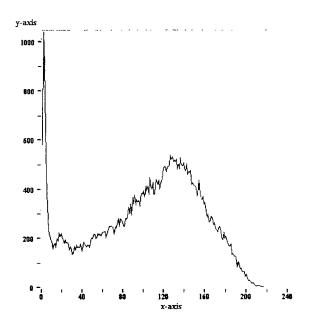


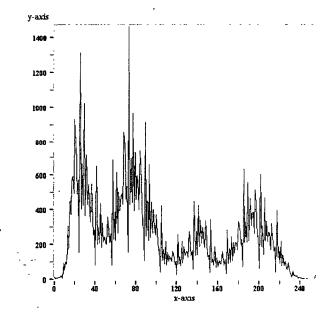
Image 1: 246×245



Histogram of Image 1



Image 2: 434×667



Histogram of Image 2

Figure 1.

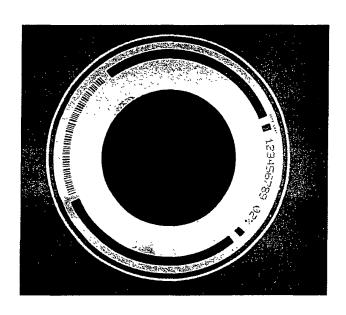


Image 3: 541×473

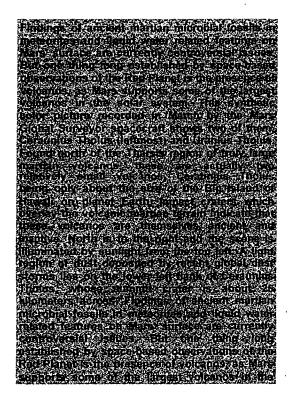
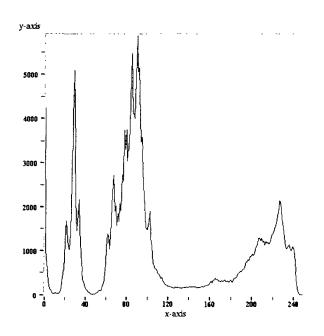
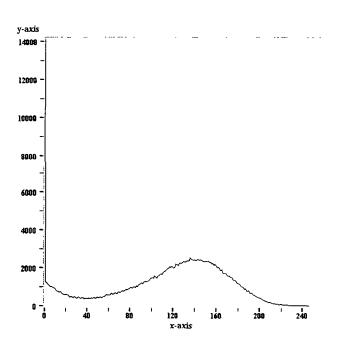


Image 4: 434×607

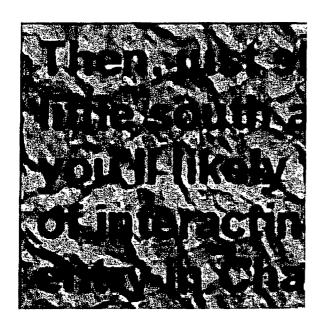


Histogram of Image 3



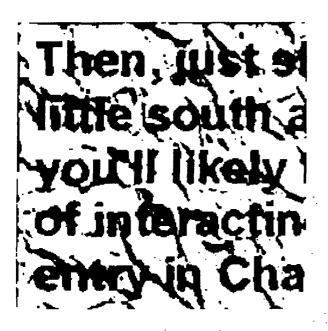
Histogram of Image 4

Figure 2.



Original 8-Bit Gray Scale: Image 1

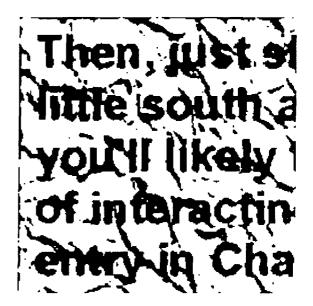
Image Size: 246×245



Huang-Wang Binarization Method

CPU Execution Time: 10.8 ms

Optimal Threshold: 89



Otsu's Binarization Method

CPU Execution Time: 1.5 ms

Optimal Threshold: 88

Then, just slattle south a you'll likely to of interactine entry in Cha

Proposed Binarization Method

CPU Execution Time: 2.0 ms



Original 8-Bit Gray Scale: Image 2

Image Size: 434×667



Huang-Wang Binarization Method

CPU Execution Time: 14.3 ms

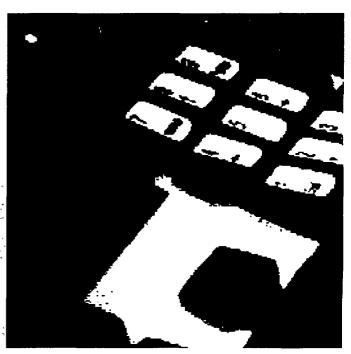
Optimal Threshold: 146



Otsu's Binarization Method

CPU Execution Time: 2.3 ms

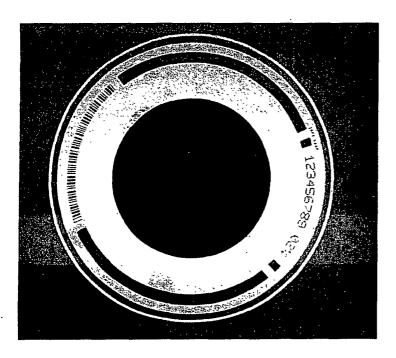
Optimal Threshold: 117



Proposed Binarization Method

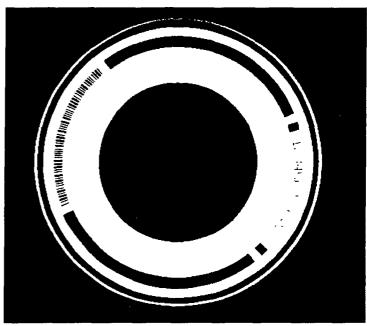
CPU Execution Time: 3.5 ms

Figure 4.



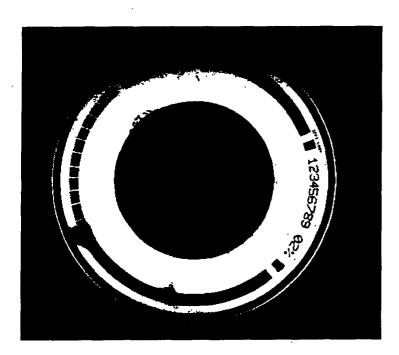
Original 8-Bit Gray Scale: Image 3

Image Size: 541×473



Otsu's Binarization Method

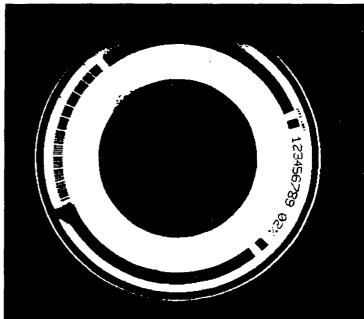
CPU Execution Time: 3.9 ms



Huang-Wang Binarization Method

CPU Execution Time: 16.1 ms

Optimal Threshold: 191



Proposed Binarization Method

CPU Execution Time: 4.0 ms

Figure 5.

Findings of ancient martial microbial tossits in meteorites and liquid water related features on Mars: surface are currently controversial issues. But-one thing-fong-established-by-space-based observations or the Red Planet is the presence of volcanos, as Mara supports some of the largest voicanos in the solar evelent this synthetic golor delice recorded in March of the Mars Global Striveyor spacecial csrows two of them. Ceraunius Tholus Leftmost) and Uranius Tholus. Found north of the Tharsis region of truly large martign - yelcangs , these are actually two relatively small volcanos ceratrilis fficilis being coly: about the sale of the signs land of Save pront planet. Earth: proper contess which overlay the sepicanic matten terrain indicate that these volcanos are themselves ancient and

Original 8-Bit Gray Scale: Image 4

Image Size: 434×607

Findings of ancient martian microbial foss meteorites and liquid water related feature Mars' surface are currently controversial is But one thing long established by space-t observations of the Red Planet is the presen volcanos, as Mars supports some of the la volcanos in the solar system. This synt color picture recorded in March by the Global Surveyor spacecraft shows two of I Ceraunitis Tholus (leftmost) and Uranius Th Found north of the Tharsis region of truly martian volcanos, these are actually relatively email voicanos Ceraunius II being only about the size of the Big Islan Hawali on planet Earth. Impact craters v overlay the volcanic martian terrain indicate

these volcarios are themselves ancient

<u>Huang-Wang Method</u>

CPU Execution Time: 15.4 ms

Optimal Threshold: 60

Findings of ancient martian microbial fossils in meteorites and liquid water related features on Mars surface are currently controversial issues. But one thing long established by space based observations of the Red Planet is the presence of volcanos, as Mars supports some of the largest volcanos in the solar system. This synthetic color picture recorded in March by the Mars Global Surveyor spacecraft shows two of them. Ceraunius Tholus (leftmost) and Uranius Tholus. Found north of the Tharsis region of truly large martian volcanos, these are actually two relatively email volcanos, Ceraunius Tholus. being only about the size of the Big Island of Hawali on planet Earth Impact craters which overlay the volcamic martian terrain indicate that these volcarios are themselves ancient and

Otsu's Binarization Method

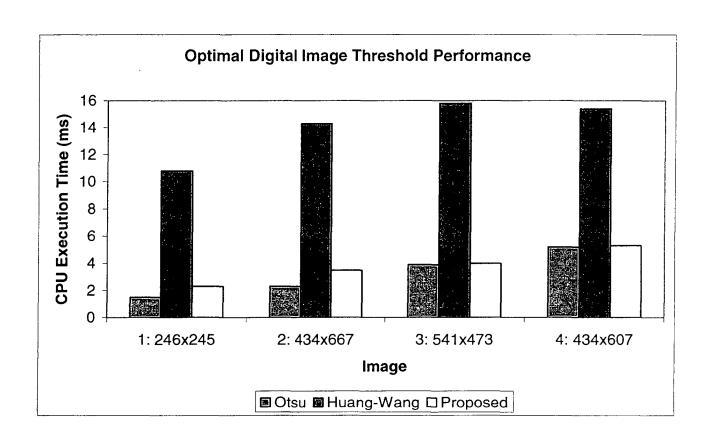
CPU Execution Time: 5.2 ms

Optimal Threshold: 89

Findings of ancient martian microbial fossils in meteorites and liquid water related features on Mars' surface are currently controversial issues. But one thing long established by space based observations of the Red Planet is the presence of volcanos, as Mars supports some of the largest volcanos in the solar system. This synthetic color picture recorded in March by the Mars Global Surveyor spacecraft shows two of them, Ceraunius Tholus (leftmost) and Uranius Tholus. Found north of the Tharsis region of truly large these martian volcanos. are actually two relatively small volcanos. Ceraunius Tholus being only about the size of the Big Island of Hawaii on planet Earth, Impact craters which overlay the voicanic martian terrain indicate that these volcanos are themselves ancient and

Proposed Method

CPU Execution Time: 5.3 ms



CPU Execution Time

Figure 7.

APPENDIX A: MATHEMATICAL FORMULATION

The image is defined as an array of fuzzy singletons corresponding to image pixels, each having a membership value associated with a certain property of the pixel. Under this assumption, an image I can be represented as

$$I = [f(x, y), \mu_I(f(x, y))]$$
(1)

For image thresholding, the membership function $\mu_I(f(x,y))$ can be defined in terms of the grade of pixel (x,y) belonging to one of the two classes, background and foreground. The membership function in each of these two classes is built based on the average gray level of each class, which is computed using the gray-level histogram as average weight factor as shown in equation 2.

$$G_1(T) = \sum_{M_{m}, Z}^{T} [zH(z)] / \sum_{M_{m}, Z}^{T} H(z)$$
(2)

$$G_2(T) = \sum_{T+1}^{MaxZ} [zH(z)] / \sum_{T+1}^{MaxZ} H(z)$$
(3)

Domain: $0 \le MaxZ$, MinZ, T, and $z \le L-1$

Where

T = Threshold value

z = Grav level

MinZ = Lowest gray level holding a nonzero histogram value MaxZ = Highest gray level holding a nonzero histogram value L = Total gray-level values; for an 8-bit image, $L = 2^8 = 256$

H(z) = Image histogram value of gray level z

 $G_1(T)$ = Average gray-level value for class 1 (background) $G_2(T)$ = Average gray-level value for class 2 (foreground)

The membership function is linear-triangular-type as shown below and defined as

$$\mu_{I}(z) = \begin{cases} [z - MinZ] / [G_{1}(T) - MinZ] & \text{if } MinZ \leq z \leq G_{1}(T) \\ [T - z] / [T - G_{1}(T)] & \text{if } G_{1}(T) < z \leq T \\ [z - T] / [G_{2}(T) - T] & \text{if } T < z \leq G_{2}(T) \\ [MaxZ - z] / [MaxZ - G_{2}(T)] & \text{if } G_{2}(T) < z \leq MaxZ \end{cases}$$

$$(4)$$

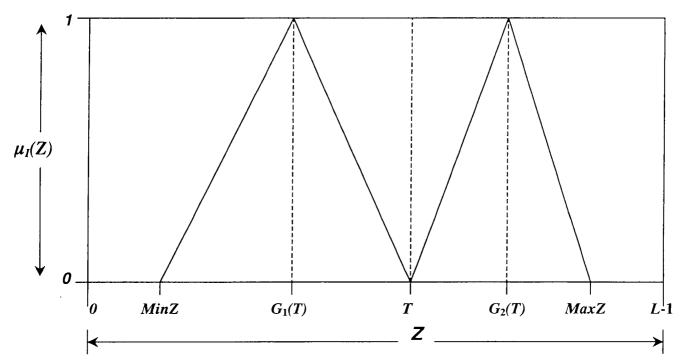


Figure 1. Membership Function

The entropy measure is used as a cost function for the selection of the optimal image threshold. It is defined using the histogram information as

$$S(T) = \left\{ 1 / \left[M N \log 2 \right] \right\} \sum_{M_{I} \in \mathcal{I}}^{M a \times Z} H(z) Se\left[\mu_{I}(z) \right]$$
 (5)

Where

S(T) = Entropy measure

M = Image rows (number of horizontal pixels)
 N = Image columns (number of vertical pixels)

 $Se[\mu_I(z)]$ = Entropy factor

A simple linear function with negative slope is selected to calculate the entropy factor since the entropy measure should decrease as the membership value increases (as the fuzziness becomes smaller). The linear function is shown in figure 2.

The threshold is chosen to minimize S(T), that is

$$T_{OPTIMAL} = arg \ min \ S(T) \text{ where } MinZ \le T \le MaxZ$$
 (6)

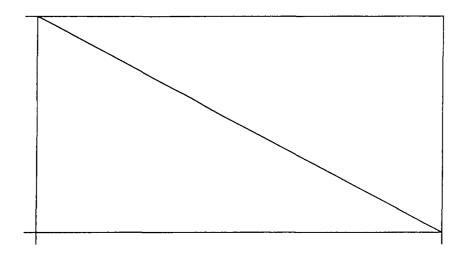


Figure 2. Entropy Factor